**Too much (information) to learn: Social learning, culture, and a case study of declining FLFP in India**

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# 1 Introduction

In most learning models in economics having access to more information leads to a better economic outcome for the economic agents. However, scenarios where access to loads of information leading to worse outcomes are ubiquitous in real life. Many recent papers have addressed the issue of this information overload.

For example, Persson (2017) shows that having access to information from infinitely many competitive senders indeed worsen the payoff obtained by the receiver. Because of the information overload, she chooses to ignore the information and go with her prior. Gagnon-Barstch et al (2018) showed that having access to the full history of actions and signal leads to a worse outcome for the decision-maker since she overlooks important data related to the decision and never learns about her mistake.

In this paper, I consider a similar learning failure caused by access to social learning, i.e., information from neighbors. Our case study deals with the labor market decision on Indian women. I assume that the women do not know perfectly there return from joining the labor force. There are two types of women who have different payoff from joining the labor force and a rational agent would only join the labor force if her expected gain is greater than zero.

Similar to earlier papers I assume that the decision-maker (DM) faces a cost to learn or pay attention to the expected payoff from working and would only venture to learn (or experiment) if her prior belief is the learning will be worth undertaking. In this scenario, the woman can always observe the action of other women from the earlier generation. This generates a belief over possible type distribution and a belief over her possible type.

If she observes that most women are working (or not working) in the last generation she updates her belief that most women are of the type that has higher payoff from working (or not working) which also increases her chance of being more likely of the more productive (less productive) type. The stronger the evidence from social learning she gets the smaller are her incentives from learning further. Since I assume joining labor force is a one-time decision, no women would learn perfectly about her payoff before she makes her choice.

This implies if a woman is born in an economy earlier women were overly optimistic (or pessimistic) about the payoff from joining labor force (compared to the true type distribution) and women learn socially from their predecessors then the optimism (or pessimism) would propagate

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and the economy would not reach its true distribution even in the long run.

I apply this model of learning to understand the labor market behavior of Indian women. Despite the recent growth and development experience of India during the past few decades, one of the significant features that prevail is that of gender difference in various socio-economic activities. One crucial example of gender difference can be observed in the rate of labor force participation. Compared to many other developing countries, India has a significantly lower female labor force participation rate. In 2014, India ranked 17th from the bottom in terms of female labor force participation for women of ages 15+, with a value of 27% according to the World Bank survey of World Development Indicators.

Despite having a significantly low female labor force participation (FLFP) rate, India is also observing a steady decline in the FLFP since 1987. Figure 1 shows the declining trend of female labor force participation in India post-2006. The same trend is also found from the national sample survey dataset as well (refer table 4). Despite having a growth rate of around 7% per year, the Indian labor force has not yet gone through its phase of *feminization*.

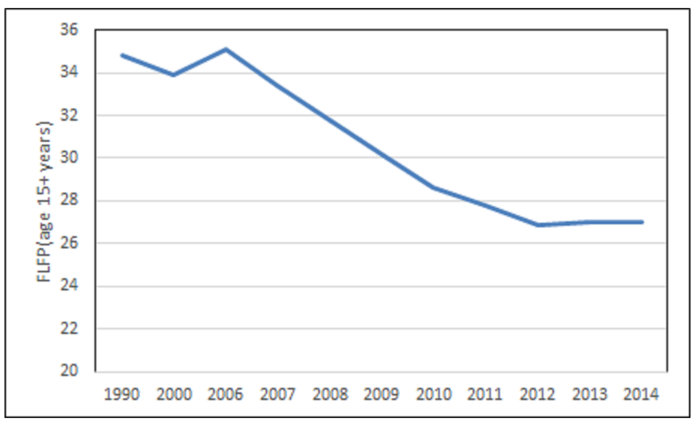



Figure 1: Labor force participation, female(% of female population ages 15+)

Several recent papers have discussed the trend in female labor participation in different Asian countries and India is an outlier amongst her neighbors. In general, the South Asian countries (Bangladesh, India, Pakistan and Sri Lanka) has a relatively low labor force participation rate (around 30% in 2016) compared to the world average, but no other country in the region is experiencing a decline in female labor force participation rate except India. In Bangladesh, the FLFP has increased in the 2000s due to the growth of the textile industries. Pakistan has also started to experience an increase in FLFP starting from a very low value. Lack of education and household duties are considered as the main reason behind the low participation of Pakistani women. Sri Lanka, on the other hand, has experienced a low and stagnant level of FLFP along with a high level of development.

On the other hand in East Asia, however, such a decline in FLFP is observed for some countries. For example, in China, the FLFP has fallen starting from a much higher level, around 60%. One explanation attributed to the decrease in FLFP is the lack of demand for the female worker, especially in the manufacturing sector. Similar to India, Chinese women are also mostly hired in the agriculture and service sector and are under-represented in the manufacturing industry. This can create a lack of demand for female labor and the substantial gender wage gap as the composition of sectors change. However, I will discuss below India female labor market faces a somewhat different situation. A high growth rate of GDP, higher female education and lower fertility have accompanied a low and declining FLFP.

Several theories have been offered for the explanation of the low level and decline. Both demand and supply-side factors contribute to the labor market decisions of Indian women. Previous studies have discussed the role of education, fertility, family size, increasing household productivity due to education, sectoral composition, and disparate job growth, etc in the labor market decision of women. In this paper, I offer an additional factor for low and declining FLFP, namely the role of culture. Following Fernandez (2018) I define "culture" as the aggregate belief and preferences over the labor market decision for women. The aggregate belief and preferences are known to women by social learning. Thus culture and social learning are equivalent in my discussion.

If a girl grows up in a neighborhood where it is not acceptable for women to work outside home, her prior belief is the payoff from working outside the home is substantially small to justify further learning about the actual payoff. This discouragement of further learning leads to having more pessimistic belief and can cause a steady decline in FLFP.

To measure the impact of culture I define a variable stigma that is measurable for the economy. I have constructed the measures of stigma based on two types of survey responses. First, the Indian Human Development Survey (IHDS) data that asks questions regarding standard practices in society, and second, the World Values Survey (WVS) which asks about the respondents' beliefs, attitudes, and preferences regarding various gender-related social issues.

In both cases, I have selected questions related to women in the workforce and more generally about the role of women outside the home. Using both datasets, it has been found that the aggregate belief has become more unfavorable for women in India during the period 1990-2012. The role of culture has been discussed in several gender-related contexts for many other countries. For example, culture has been used as an explanatory variable for the dynamics of labor force participation rate of married women in the US.

In the empirical analysis, I test the implications of the model by exploiting the state-level heterogeneity in culture. I show that after controlling for individual, household and state-level factor culture has a statistically significant positive relationship with the level of FLFP and differential impact on immediate and lagged change in FLFP assuming the prior belief is biased against joining the labor force.

The organization of the rest of the paper is as follows; Section section 2 describes the theoretical model. Section 3 describes the main datasets used in the study and discusses the empirical strategy and reports the main empirical results, and section 4 discusses alternate hypotheses. A literature review is given in 5 and section 6 concludes.

# 2 Theoretical Framework

## 2.1 Environment

Let us consider that time is discrete and infinite, $t = \{1, 2, \ldots, \infty\}$. We consider an economy is divided into $D$ neighbourhoods. In each period $t$ a measure $m_d$ of women enter the neighbourhood $d$ for $d \in \{1, \ldots, D\}$.

Upon entering the economy in period $t$, the DM has two actions to choose from, to join the labor force, namely $l$, or not to join the labor force, namely $n$. Let us define $A = \{l, n\}$ to be the set of actions. Joining the labor force includes both working for payment and searching for jobs. Whereas being not in the labor force includes attending an educational institution, home production without payment and leisure. The important distinction between the two actions is that if an agent chooses $l$, she is willing to work for payment and if she chooses $n$ she is not willing to work for payment.

Let $L_{dt}$ denote the proportion of women choosing $l$ in period $t$ and neighbourhood $d$. Thus $L_{dt}$ in this model denotes the female labor force participation rate in a neighbourhood.

The agents are rational, i.e., they will join the labor force if the payoff from choosing $l$ is higher than that of choosing $n$. The payoff of choosing $l$ is however not restricted to the expected wage payment. Following Fernadez(2013) I assume the payoff from joining $l$ is the long-run utility from working for pay. This includes the utility from changing bargaining power, impact on child development among others.

We assume there are two types of woman, namely $H$ and $L$ in the economy and the payoff from joining the labor force depends on the type of the woman. However, the woman herself does not know her type but can learn about it subject to a cost of learning. For an individual DM let $\omega_H$ denotes the state where her type is $H$ and $\omega_L$ denotes the state where her type is $L$. The payoff relevant idiosyncratic state space is thus given by the set $\Omega = \{\omega_H, \omega_L\}$.

Let us assume that DMs in any period $t$ is drawn from stationary data generating process $\mu^* \in \Delta(\Omega)$. However, the DMs need not know the true data generating process and DMs in neighbourhood $d$ instead enter with a prior belief $\mu_0 \in \Delta(\Omega)$ such that $supp(\mu^*) \subseteq supp(\mu_{0,d})$. Since all women are ex-ante identical $\mu_{0,d}$ denotes the probability of being type $H$ in neighbourhood $d$. For simplicity we assume that $\mu_{0,d}$ is stationary for a given neighbourhood $d$.

Along with the type of the women, her payoff from joining the labor force also depends on a set of observed aggregate and idiosyncratic variables, denoted by the set $X\mathbf{X}_O$. Examples of the aggregate variables are current unemployment rate in the neighborhood and/or in the entire economy, government policies facilitating female employment, relative growth rate of different sectors, availability of formal childcare system, types of jobs offered to women, safety in the workplace, etc. Examples of idiosyncratic variables are education, work experience, household income, marital status, number of children, informal childcare support from family, etc.

Finally, culture represents an unobserved aggregate variable that is payoff relevant to the women's labor market decision. Narrowly defined in this model culture represents beliefs and preferences held by agents in neighborhood $d$ over the action space $\mathbf{A}$.

Thus culture has two relevant components here. First, a shock to culture can affect actual payoff from joining the labor force. Second, culture is also represented by the belief over expected payoff from joining the labor force. Note that, neither the societal preference nor the shared belief is observed directly by the DM. For simplicity let there be only two culture states namely, $\mathbf{C} = \{c_H, c_L\}$. Similar to learning about $\Omega$ the DM can learn about $\mathbf{C}$ in period $t$ subject to a cost of learning. Let $p_{0,d}$ denote the stationary prior belief that $c = c_H$ for neighbourhood $d$. We assume $\Omega$ and $\mathbf{C}$ are independent.

Let $u : \mathbf{A} \times \Omega \times \mathbf{C} \times \mathbf{X}_O \to \mathbb{R}$ denote the utility function. Furthermore, let the utility form chooing $n$ be normalized to 0 for all states. Whereas the utility from choosing $l$ is as follows:

$$
\begin{aligned}
u(l, \omega_i, c_j, o_k) &= \underbrace{u_U(\omega_i, c_j)}_{\text{unobserved}} + \underbrace{u_O(o_k)}_{\text{observed}} \\
u_U(\omega_i, c_j) &= \underbrace{u_I(\omega_i)}_{\text{idiosyncratic type}} + \underbrace{u_C(c_i)}_{\text{culture}}
\end{aligned}
$$

where

$$u_I(\omega_H) = \overline{u}, \quad u_I(\omega_L) = \underline{u}, \quad \overline{u} > 0 > \underline{u}$$

and

$$u_C(c_H) = c > 0, \quad u_C(c_L) = 0$$

The timeline for the choice problem is as follows:

1. DM enters with prior $(\mu_{0,d}, p_{0,d})$ over $\Omega \times \mathbf{C}$ at the beginning of period $t$
2. DM obsereves the realization of $\mathbf{X}_{O,t}$
3. DM observes the realization of $L_{d,t-1}$ (except time $t = 0$ DMs) and updates her belief to $(\mu_{1,d}, p_{0,d})$ over $\Omega \times \mathbf{C}_t$
4. DM pays the cost of learning and updates her belief over $\Omega \times \mathbf{S}$
5. Given her posterior belief DM chooses an action to maximize her expected payoff
6. Payoff is realized and DM leaves

## 2.2 Learning problem

In this model, the DM has access to two types of information, namely social learning, and private learning. The information obtained by the two types of learning are significantly different and has a disparate impact on the DM's decision. The DM is Bayesian, i.e., she updates her belief following Bayes rule.

The information structure associated with social learning by a DM in period $t$ is characterized by the observation of the realized value of $L_{dt-1}$. Note that, in the set $\mathbf{X}_O$ some idiosyncratic variables are only observed by the DM. Thus even though these variables are observed by the DM in period $t-1$, when a DM in future period observes her choice she does not observe the realization of these variables.

To avoid this complication I assume that the distribution of realized $\mathbf{X}_O$ in period $t-1$ is common knowledge in period $t$. However, the realization of $C_{t-1}$ is not observed by the DM in period $t$. Since the DMs are drawn randomly from a stationary data genrating process $\mu^*$ which is unknown to the DM, upon observing $L_{dt-1}$ the DM updates her belief over $\mu \in \Delta(\Omega)$. By law of large numbers thus upon observing $L_{dt-1}$ the DM in period updates her belief over $\Delta(\Omega) \times \mathbf{C}_{t-1,d}$ given $(\mu_{0,d}, p_{0,d})$. Social learning is not costly and exogenous, i.e., upon observing $L_{dt-1}$ the DM will necessarily update her belief over $\Delta(\Omega) \times \mathbf{C}_{t-1}$.

Whereas social learning provides information about economy-wide data generating process $\mu \in \Delta(\Omega)$, private learning is informative about idiosyncratic state $\Omega$. Furthermore, I assume no correlation structure between $C_{t-1}$ and $C_t$ hence, social learning is informative about the realization of $C_{t-1}$ whereas private learning is informative about $C_t$. Also, unlike social learning, private learning about $\Omega \times \mathbf{C}_t$ is costly, and the cost of learning depends on the informativeness of signal structure.

However, instead of assuming that the DM is choosing a signal structure I assume that the DM directly chooses the distribution of posterior beliefs for each relevant states. Due to the Blackwell informativeness criterion, there is a one-to-one mapping between choosing a signal structure and distribution of posterior beliefs (see Matejka and McKay (2015), for example). So an information structure in this model is a distribution of beliefs over the joint space, i.e., $\gamma \in \Delta(\Delta(\Omega \times \mathbf{C}_t))$.

The cost of learning takes the form of Shannon relative entropy. Let $P(j)$ denote the prior or unconditional probability of choosing action $j \in A$ based on the belief $(\mu_{1,d}, p_{0,d})$ and observation $\mathbf{X}_{O,t}$ and $P(j|\omega_i, c_j)$ be the posterior or conditional probability of choosing action $j \in A$ in state $(\omega_i, c_j)$. The cost function then can be written as,

$$K\left(\lambda, \mu_{1,d}, p_{0,d}\right) = \lambda \left\{ \underbrace{\sum_{\omega_i \times c_j \in \Omega \in \mathbf{C}_t} \mu_{1,d} p_{0,d} \sum_{j \in A} P\left(j|\omega\right) \ln P\left(j|\omega\right)}_{\text{expected entropy of the posterior}} - \underbrace{\sum_{j \in A} P\left(j\right) \ln P\left(j\right)}_{\text{entropy of the prior}} \right\}$$

where $\lambda_d \in [0, \infty]$ is the marginal cost of private learning. For simplicity I assume that the parameter $\lambda$ is same across all DM in the economy. [1]

[1] The theoretical results remain true even if $\lambda$ varies across individual agents but the distribution of $\lambda$ is independent of the state $\Omega \times \mathbf{C}_t$ and the distribution is common knowledge.

### 2.3 Agent's Optimization

The agent's optimization problem is to choose a distribution of posterior probabilities of choosing different actions to maximize the net expected payoff of the agent,

$$\max_{\left\{P(k|\omega)\right\}_{\omega\times c_j\in\Omega\times\mathbf{C}_t}} E_{(\mu_{1,d},p_{0,d})}u(k,\omega_i,c_j)-K(\lambda,\mu_{1,d},p_{0,d}).$$

We will solve the DM's the problem backwards, i.e., given the private learning strategy of each DM we will find $(\mu_{1,d},p_{0,d,t-1})$ upon observing $L_{dt-1}$ using Bayes rule. Following Matejka and McKay(2015), the solution to the agent's optimization problem is similar to a logistic model of random utility. For any time $t\geq 0$ agents, the posterior probability of choosing action $l$ in state $(\omega_i,c_j)$ would be,

$$P\left(l|\omega_i,c_j\right)=\frac{P\left(l\right)exp(\frac{u\left(j,\omega_i,c_j\right)}{\lambda})}{P\left(l\right)exp(\frac{u\left(j,\omega_i,c_j\right)}{\lambda})+1-P(l)},\forall(\omega_i,c_j)\in(\Omega\times\mathbf{C}_t) \tag{1}$$

Bayesian plausibility implies given the initial belief $\mu_{dt}$

$$\sum_{\omega\times c_j\in\Omega\times\mathbf{C}_t}\mu_{1,d}p_{0,d}\frac{\exp\Big(u\left(l,\omega_i,c_j\right)/\lambda\Big)}{\sum_{k\in A}P\left(k|\omega_i,s_j\right)\exp\Big(u\left(k,\omega_i,s_j\right)/\lambda\Big)}\leq 1\quad\forall j\in A. \tag{2}$$

The inequality holds with equality if $P\left(j|\omega\right)>0$.

Given the posterior choice probability the log-likelihood ratios for all four states in $\Omega\times\mathbf{C}$. The four log-likelihood ratios are as follows:

$$\begin{aligned}
\ln\frac{P(l|\omega_H,c_H)}{P(n|\omega_H,c_H)}&=\ln\frac{P(l)\exp\left(\overline{u}+c\right)}{P(n)}=\ln\frac{P(l)}{P(n)}+\frac{\overline{u}+c}{\lambda}\\
\ln\frac{P(l|\omega_L,c_H)}{P(n|\omega_L,c_H)}&=\ln\frac{P(l)\exp\left(\underline{u}+c\right)}{P(n)}=\ln\frac{P(l)}{P(n)}+\frac{\underline{u}+c}{\lambda}\\
\ln\frac{P(l|\omega_H,c_L)}{P(n|\omega_H,c_H)}&=\ln\frac{P(l)\exp\overline{u}}{P(n)}=\ln\frac{P(l)}{P(n)}+\frac{\overline{u}}{\lambda}\\
\ln\frac{P(l|\omega_L,c_H)}{P(n|\omega_L,c_H)}&=\ln\frac{P(l)\exp\underline{u}}{P(n)}=\ln\frac{P(l)}{P(n)}+\frac{\underline{u}}{\lambda}
\end{aligned}$$

Given the private learning strategy we can now compute the belief upon social learning as follows. Let $\mu_{0,d}=\int_0^1 G(\mu)d\mu$ be the a priori expected value of $\mu$. If the observed value of female labor force participation is $L_{dt-1}$ then by Bayes rule

$$P(\mu,c_{H,t-1}|L_{dt-1})=\frac{P(L_{dt-1}|\mu,c_H)G(\mu)p_{0,d}}{p_{0,d}\int_0^1 P(L_{dt-1}|\mu,c_H)G(\mu)d\mu+(1-p_{0,d})\int_0^1 P(L_{dt-1}|\mu,c_L)G(\mu)d\mu}$$

Hence,

$$\mu_{1,d} = E(\mu|L_{dt-1}) = \int_0^1 P(\mu, c_H|L_{dt-1})G(\mu) + d\mu \int_0^1 P(\mu, c_L|L_{dt-1})G(\mu)d\mu$$

Given the private learning strategy of the DMs we get

$$P(L_{dt-1}|\mu, c_H) = \frac{\mu P(l)\exp\left((\overline{u}+c)/\lambda\right)}{P(l)\exp\left((\overline{u}+c)/\lambda\right)+1-P(l)} + \frac{(1-\mu)P(l)\exp\left((\underline{u}+c)/\lambda\right)}{P(l)\exp\left((\underline{u}+c)/\lambda\right)+1-P(l)}$$

and

$$P(L_{dt-1}|\mu, c_L) = \frac{\mu P(l)\exp\left(\overline{u}/\lambda\right)}{P(l)\exp\left(\overline{u}/\lambda\right)+1-P(l)} + \frac{(1-\mu)P(l)\exp\left(\underline{u}/\lambda\right)}{P(l)\exp\left(\underline{u}/\lambda\right)+1-P(l)}$$

Since $c > 0$, the distribution $P(L_{dt-1}|\mu, c_H)$ first order stochastically dominates $P(L_{dt-1}|\mu, c_L)$. This implies $E(\mu|L_{dt-1})$ is increasing in $L_{dt-1}$, i.e., a higher value of $L_{dt-1}$ generates a higher $\mu_{1,d}$.

Again from the private learning behavior of the DM we get $P(l|\omega_i, c_j)$ is increasing in $P(l)$ where by Bayesian plausibility

$$P(l) = \mu_{1,d}P(l|\omega_H) + (1-\mu_{1,d})P(l|\omega_L),$$

which is also increasing in $\mu_{1,d}$ by symmetry of the Shannon cost function.

### 2.4 Testable Implication

Consider two neighbourhoods 1 and 2 that has identical sequence of $\{\mathbf{X}_{O,s}\}_{s\leq t}$, $\{\mathbf{C}_s\}_{s<t}$ and same $\mu^*$ but in period $t$ neighbourhood 1 has a higher value of $\mathbf{C}$, i.e., $\mathbf{C}_{t,1} = c_H$ and $\mathbf{C}_{t,2} = c_L$. We want to compare the sequence of $L_{dt^{prime}}$ for $t^{prime} \geq t$ for the two neighbourhood.

**Implication 1.** *If the sequence of $\{\mathbf{X}_{O,s}\}_{s>t}$ and $\{\mathbf{C}_s\}_{s>t}$ are same for both two neighbourhoods then $L_{1t'} > L_{2t'}$ for any $t' \geq t$.*

Implication 1 states that a one-period shock to $\mathbf{C}_t$ will have a long-run impact over the entire sequence of $L_{dt'}$ even when the two neighborhoods are identical in every possible way and the DM in period $t$ only observes the realized value of $L_{dt-1}$ only one period prior.

Note that, if $L_{1t} > L_{2t}$ then in period $t+1$ $\mu^{1,1} > \mu_{1,2}$. This implies $L_{1t+1} > L_{2t+1}$. However, $L_{1t+1} > L_{2t+1}$ would imply $\mu_{1,1} > \mu_{1,2}$ for period $t+2$ as well even for same level of $C_{t+1}$ and $C_{t+2}$ and same $\mu^*$ for both the neighbourhoods. This in turn would result in $L_{1t+2} > L_{2t+2}$ and so on.

However, the impact of $C_t$ not only has an implication on the level of $L_{dt'}$ for $t' > t$ but also the rate of change of FLFP, i.e., $L_{dt'+1} - L_{dt'}$ for $t' \geq t$ as well. Note that, since the DM chooses a signal structure to maximize her net expected payoff given her prior belief over $\Omega \times \mathbf{C}$ an increase in $\mathbf{C}_{t-1}$ always increases $P(l|\omega_i, c_j)$ irrespective of the prior belief. This implies if the DM is indeed of type $L$ then she is more lielky to mismatch when $c_{t-1}$ is higher. The relationship between the probability of two types of error and $\mathbf{C}_{t-1}$ is given in the table below,

| $\mathbf{C}_{t-1}$ | $P(n\|\omega_H, c_j)$ | $P(l\|\omega_L, c_j)$ |
|---|---|---|
| $c_H$ | $\uparrow$ | $\downarrow$ |
| $c_L$ | $\downarrow$ | $\uparrow$ |

Table 1: Error probabilities by $\mathbf{C}_{t-1}$

Now consider two neighbourhoods with same sequence $\{\mathbf{C}_s\}_{s\neq t}$ and $\{\mathbf{X}_{O,s}\}_{s>0}$. The following table represents the relationship between $\mathbf{C}_{t-1}$ and $L_{dt} - L_{dt-1}$ for both the two neighbourhoods for all possible values of $\mathbf{C}_t$,

| Neighbourhood | $\mathbf{C}_{t-1}$ | $\mathbf{C}_t$ | $L_{dt} - L_{dt-1}$ | Implication |
|---|---|---|---|---|
| $d = 1$ | $c_L$ | $c_H$ | $L_1 > 0$ | $L_1 > L_2$ |
| $d = 2$ | $c_H$ | $c_H$ | $L_2 > 0$ | |
| $d = 1$ | $c_L$ | $c_L$ | $L_3 < 0$ | $L_3 > L_4$ |
| $d = 2$ | $c_H$ | $c_L$ | $L_4 < 0$ | |

Table 2: Rate of change in FLFP between $t-1$ and $t$ by $\mathbf{C}_{t-1}$

The implications are derived from the fact that the DMs are learning about $\Omega \times \mathbf{C}_t$, i.e., the impact of $\mathbf{C}_t$ is higher than that of $\mathbf{C}_{t-1}$. Thus even after $\mathbf{C}_{t-1} = c_L$ if $\mathbf{C}_t = c_H$ then the DM would increase $P(l|\omega_i)$ for both $i \in \{H, L\}$ increasing $L_{dt}$.

Next I will consider the impact of $\mathbf{C}_{t-1}$ on the difference in FLFP for $t$ and $t+1$. For this analysis let us assume that $\mu_0 < 0.5$ i.e., $P(l) < P(n)$. By the convexity of cost function impact of $\mathbf{C}_s = c_L$ is smaller than that of $\mathbf{C}_s = c_H$ on $L_{ds+1}$. This is because even though $\mu_{1,d}|c_L < \mu_{1,d}|c_H$, for the former the total probability of mistake will be higher, i.e., the DM will be closer to the prior belief whereas for the later the probability of mistake will be lower moving the choice further away from prior belied. Under this condition if for the same two neighbourhoods (otherwise identical) we compare the difference in FLFP between $t$ and $t+1$ we obtain the following table,

| Neighbourhood | $\mathbf{C}_{t-1}$ | $\mathbf{C}_t$ | $\mathbf{C}_{t+1}$ | $L_{dt+1} - L_{dt}$ | Implication |
|---|---|---|---|---|---|
| $d = 1$ | $c_L$ | $c_L$ | $c_H$ | $L_{1L} > 0$ | $L_{1L} < L_{1H}$ |
| $d = 2$ | $c_H$ | $c_L$ | $c_H$ | $L_{1H} > 0$ | |
| $d = 1$ | $c_L$ | $c_H$ | $c_H$ | $L_{2L} > 0$ | $L_{2L} < L_{2H}$ |
| $d = 2$ | $c_H$ | $c_H$ | $c_H$ | $L_{2H} > 0$ | |
| $d = 1$ | $c_L$ | $c_L$ | $c_L$ | $L_{3L} < 0$ | $L_{3L} < L_{3H}$ |
| $d = 2$ | $c_H$ | $c_L$ | $c_L$ | $L_{3H} < 0$ | |
| $d = 1$ | $c_L$ | $c_H$ | $c_L$ | $L_{4L} < 0$ | $L_{4L} < L_{4H}$ |
| $d = 2$ | $c_H$ | $c_H$ | $c_L$ | $L_{4H} < 0$ | |

Table 3: Rate of change in FLFP between $t$ and $t+1$ by $\mathbf{C}_{t-1}$

The first implication (row 1 and 2) is true because since $L_1 > 0$, the impact of $\mathbf{C}_t = c_H$ dominates and for similar reason the fourth implication (row 7 and 8) is true because since $L_4 < 0$ the impact of $\mathbf{C}_{t-1} = c_H$ dominates. For the second and third implication the direct comparison between $t$ and $t+1$ gives the result.

| Wave | Year | FLFP |
|---|---|---|
| NSS 62 | 2005-06 | 31.8 % |
| NSS 64 | 2007-08 | 34.8 % |
| NSS 66 | 2009-10 | 24.6 % |
| NSS 68 | 2011-12 | 23.3% |

Table 4: Female labor force participation across NSS rounds, age 15-65 years

# 3 Empirical Analysis

## 3.1 Data

The three data sources used in this paper are as follows: first, the National Sample Survey (NSS) Employment and Unemployment (schedule 10) data (four rounds), second, the Indian Human Development Survey (IHDS) both 2005 and 2012 rounds and third, the World Values Survey wave (WVS, four waves) for India.

### 3.1.1 NSS 62nd - 68th Round

From NSS dataset only female respondents of ages between 15 and 65 have been considered. Previous studies on Indian female force participation have considered 15-65 as workable age for women in India. This gives a sample of size 817563 female respondents across four rounds namely NSS 62(2004-05), 64(2006-07), 66(2009-10), and 68(2011-12). There were a total of 35 states and union territories(UT) in India in 2011. Out of the 35 states and UTs, the state-level variables are not available for three regions, namely, *Daman and Diu*, *Dadra and Nagar Haveli* and *Andaman and Nicobar Islands*.

The labor force participation variable is based on both the usual principal activity status and subsidiary status variable. Based on the definition provided in the NSS dataset we define an agent to be in the labor force if she is working for pay or looking for a job as her usual principal activity status. If her usual principal status is neither working for pay or looking for jobs, then I check whether subsidiary work status. The variable lfp takes a value of 1 if the woman is in the labor force, either as her principal or subsidiary activity status, and 0 otherwise. Using this definition a woman who is still acquiring education would be considered as out of labor force unless her subsidiary status is that of working for pay. The following table shows the evolution of FLFP across different rounds.

Other individual characteristics that we use from NSS are the level of education, age, and marital status, and relationship to head. These are the categories for educational attainment; not literate, below primary, primary, middle, secondary, diploma, graduate, and post-graduate and above. There are four levels of marital status, namely, never married, married, widowed, and divorced. However, the individual level of fertility data is not available for women. The relationship to head variable works as a proxy for the bargaining power of the respondent in the household.

From NSS, we also consider household-level characteristics which include household consumption in the last 30 days measured in Rupees, religion, social group, size of the household, landholding, and sector (rural or urban). Since household income or husband's income is not available, household consumption is used as a proxy for household income. The social group consists of the scheduled tribe (ST), scheduled castes(SC), other backward castes (OBC) and others. Both the caste system and religious practices in India plays a crucial role in decision making and opportunities available to any household member.

One of the concerns for married women with small children in the lack of informal childcare support previously obtained through larger family units. The size of the household is a proxy for that. Since the average rate of fertility has been around 2.4 births per woman in the past decade, a family of size smaller than five would be unlikely to have sufficient childcare support. On the other hand, a large family may also imply the married women would be living with her in-laws family in which case she would have less freedom of choice, both concerning fertility and work. The details of the individual and household level variables are given in the appendix.

The aggregation is done at the State level. There is considerable heterogeneity across states in terms of female LFP and other aggregate level variables(See Appendix table **??** for example). For States, we use the GSDP, the growth rate of the industry for each relevant financial year. The other State-level variables are culture variables constructed from different datasets.

### 3.1.2 IHDS 2005 and IHDS 2012

From the IHDS dataset, the women questionnaire regarding gender relations has been used here as a measure of culture. Here I define culture narrowly as the aggregate (neighborhood level) belief and preferences towards the working status of women. The respondents are married women of age above 15. The responses for all 35 states and UTs mentioned before are recorded in the IHDS dataset. The gender relation (GR) questions report the standard practice in the community of the respondent. Note that this is not about the belief of the respondent and reflects actual practices in the respondents family and neighborhood.

There are five categories of questions that we have considered here, decision making power in the household, whether permission is required to go out, work-related decision making power, conservative family practices and financial independence of the woman. These five sets of questions together reflect the obstacles that women might face when working outside the home.

The first variable is regarding who makes most decisions in the household ($GR1G - GR8G$ in 2012 and $GR1G : GR5G$ in 2005). The decision making includes everyday activities like cooking ($GR1G$) and what to do when the respondent falls sick ($GR4G$) or the children fall sick ($GR7G$) to more important decisions regarding buying expensive items ($GR2G$), number of children ($GR3G$), buying property ($GR5G$) to marriage of the children ($GR6G, GR8G$).

The second variable is whether the woman can go out without permission from anyone else in the household ($GR9A - GR12A$ in 2012 and $GR6G : GR8G$ in 2005). The women may require permission to go to healthcare center ($GR9A$), local shop ($GR11A$), a friend's or relative's house

($GR10A$) or a short distance by train or bus ($GR12A$). Saha (2016) reported a survey response regarding labor market condition for women in selected urban towns and rural villages in two Indian states, namely Gujarat and Uttar Pradesh. The survey showed that one of the significant obstacles for women employment is the lack of freedom to go outside. This variable measures how easy it would be for a woman to go outside her home.

The third variable states who make the decision related to work for the women ($GR47$). This is only available for IHDS 2012 round. Since financial independence affects the bargaining power in a household the freedom to make decisions regarding whether or not to work can be crucial for labor force participation decision.

The fourth variable is regarding family practices, in particular, one of the most prevalent conservative family practice in India, namely, the practice of *pardah /pallu/ burkah* which requires the woman to cover her face. This is practiced across various religious and social groups ($GR20$ in 2012 and $GR9$ in 2005) and is often a hindrance for many occupations affecting the labor force participation decision.

The fifth variable is whether the respondent owns a bank account in her name or not ($GR27H$) in 2012 and $GR15B$ in 2005). The rollout of MGNREGA programs requires eligible participants to have a bank account. Also, bank accounts reflect the financial freedom and bargaining power of the women in the family.

Combining all five categories with equal weights, we finally create the variable *culture* to measure the stigma against women. A higher value of the variable indicates a lower level of stigma and in more conducive for the woman to work for pay. There are few other gender relation variables that we do not include in our analysis, namely domestic violence and the safety of women in the neighborhood. Since the labor force participation is most likely to affect both these two variables directly, they are not incorporated in the measure of stigma.

The first round of IHDS was conducted in 2005 with a similar set of questions. The questions regarding who decides work are not in the 2005 round, so we do not have *state_dw* for 2005. Also, some questions regarding decision making are not asked in the 2005 survey. Taking into account of these differences we have constructed the four aggregating variables using IHDS 2005 dataset. The following table,(see table **??**) shows the overall countrywide comparison of the four different variables.

### 3.1.3 WVS round 6(2012)

WVS round 6 has been conducted in 2012 and covers 4078 respondents from 17 states of India. All respondents are above 18 years, and 44% of them are female. We have selected the following survey questions specifically related to women and gender relations for working women,

1. $V45$ : "Jobs are scarce; men should have more rights to jobs."; agree, neutral or disagree?

2. $V47$ : "If a woman earns more money than her husband, it's almost certain to cause problems"; agree, neutral or disagree?

3. $V48$ : “Having a job is the best way for a woman to be an independent person.”; agree, neutral or disagree?

4. $V50$ : “When a mother works for pay, the children suffer.”; strongly agree, agree, disagree or strongly disagree?

5. $V51$ : “On the whole, men make better political leaders than women.”; strongly agree, agree, disagree or strongly disagree?

6. $V52$ : “A university education is more important for a boy than for a girl.” strongly agree, agree, disagree or strongly disagree?

7. $V53$ : “On the whole, men make better business executives than women do. “; strongly agree, agree, disagree or strongly disagree?

8. $V54$ : “Being housewife is as satisfying as working for pay.”; strongly agree, agree, disagree or strongly disagree?

Similar set of questions have been asked in the earlier rounds of WVS in India. The next table shows the percentage of people agreeing or strongly agreeing with the statement across different WVS rounds between 1995-2012,

For each of the states covered in the WVS round 6, the proportion of people agreeing or strongly agreeing has been recorded and the arithmetic mean of these four proportions is constructed for each state. This gives a single number which would be called *state_s*, for each state under consideration. This variable is considered as a measure of stigma against working women in that state. All states have been divided into two groups based on this variable *state_s*.

One major disadvantage of the WVS data is that it only covers 17 out of 35 states and UTs in India. As a result, we lose about 27% of the respondents from NSS data. However, the WVS goes back to 1995 (compared to IHDS which only goes back to 2005) and considers both genders as respondents. Hence, I use WVS data to report the trend in culture but does not include it in the main specification.

### 3.2 Empirical Strategy

We use the empirical strategy to test the implications from the theoretical model. The three implications we want to test are as follows:

1. A higher level of culture variable will increase FLFP

2. A higher level of culture variable will decrease the immediate change in FLFP

3. A higher level of culture variable will increase the future change in FLFP

There is significant heterogeneity across the Indian states across many important dimensions. Figure 3 shows that the FLFP and rate of change of FLFP vary significantly across the Indian

| | WVS 3(1995) | WVS 4 (2001) | WVS 5(2006) | WVS 6(2012) |
|---|---|---|---|---|
| Jobs are scarce; men should have more rights to jobs | 45.44 | 50.55 | 50.52 | 52.38 |
| If a woman earns more money than her husband, it's almost certain to cause problems | 46.86 | NA | NA | 34.09 |
| Having a job is the best way for a woman to be an independent person. | NA | NA | NA | 35.21 |
| When a mother works for pay, the children suffer.[a] | 55.1 | 50.5 | NA | 75.85 |
| On the whole, men make better political leaders than women. | 41.62 | 50.45 | 53.07 | 51.96 |
| A university education is more important for a boy than for a girl. | 28.33 | 35.91 | 38.63 | 35.24 |
| On the whole, men make better business executives than women do. | NA | NA | 48.13 | 50.93 |

Table 5: Percentage of Respondents Agreeing or Strongly Agreeing

[a] In the earlier rounds the question was "A working mother can establish just as warm and secure a relationship with her children as a mother who does not work"

states. The level of culture as measured from IHDS and WVS datasets also vary across states. I define Indian states as relevant neighborhoods and use the state-level heterogeneity to test the implications.

### 3.3 OLS model

The first specification considers an OLS estimate of labor force participation by a female member of the household pooling data across 4 NSS rounds, namely NSS 62, 62, 66 and 68. The equation to be estimated is as follows:

$$Pr\ (l|\omega) = \beta_0 + \beta_1 culture + \beta_i' \mathbb{X}_i + \beta_h' \mathbb{X}_h + \beta_s' \mathbb{X}_s + \eta. \tag{3}$$

Where *culture* is measured from the IHDS 2005 and 2012 data for relevant rounds of NSS. The variable $\mathbb{X}_i$ represents individual characteristics, namely, level of education, age, marital status. The variable $\mathbb{X}_h$ represents household-level characteristics namely religion, social group (SC, ST, and OBC), consumption group quartiles, which serves as a proxy for household income quartiles and household size, land holdings, and sector (rural or urban). Finally, $\mathbb{X}_s$ represents the state or *neighbourhood* level characteristics, namely, GSDP and growth rate of the industry in the state.

The first implication predicts $\beta_1 > 0$, i.e., a higher value of culture will increase the probability of joining the labor force.

### 3.4 Logistic Model

To test the first implication I also run a *logistic regression* with *culture* as the independent variable of interest. Using the theoretical model we run the following regression:

$$\log \frac{Pr\ (l|\omega)}{Pr\ (n|\omega)} = \beta_0 + \beta_1 culture + \beta_i' \mathbb{X}_i + \beta_h' \mathbb{X}_h + \beta_s' \mathbb{X}_s + \eta \tag{4}$$

The dependent variables are same as that of the OLS specification. Here also, the theory predicts $\beta_1 > 0$.

### 3.5 Immediate change in FLFP

For implication 2 I have run state level OLS regression of the change in FLFP between two NSS rounds, namely, 64th round (2007-08) and 62th round (2005-06) using $culture\_IHDS\_2005$ as the main independent variable. This gives the following OLS regression,

$$L_{dt+1} - L_{dt} = \beta_0 + \beta_1 Culture\_IHDS\_2005 + \beta_{2,t} \mathbb{X}_{S,t} + \beta_{2,t+1} \mathbb{X}_{S,t+1} + +\epsilon. \tag{5}$$

Implication 2 that $\beta_1 < 0$, i.e., the states with higher culture should experience a lower change in FLFP between 2005-06 and 2007-08 (this is the impact on immediate change).

### 3.6 Future change in FLFP

For implication 3 I have run the same OLS regression but for rounds, NSS 68 and 66 and NSS 68 and 64 to estimate the impact of $culture\_IHDS\_2005$ on future changes in FLFP. The specification is as follows

$$L_{dt+2} - L_{dt+1} = \beta_0 + \beta_1 Culture\_IHDS\_2005 + \beta_{2,t+1}\mathbb{X}_{S,t+1} + \beta_{2,t+2}\mathbb{X}_{S,t+2} + +\epsilon. \tag{6}$$

$$L_{dt+2} - L_{dt} = \beta_0 + \beta_1 Culture\_IHDS\_2005 + \beta_{2,t}\mathbb{X}_{S,t} + \beta_{2,t+2}\mathbb{X}_{S,t+2} + +\epsilon. \tag{7}$$

The model predicts that $\beta_1 > 0$, the lagged impact of culture is positive.

### 3.7 Results

The results from the above four specifications are as follows:

| | *Dependent variable:* | |
|---|---|---|
| | FLFP | |
| | OLS | Logistic |
| Culture | 0.143*** | 0.296*** |
| | (0.006) | (0.030) |
| Invidividual | ✓ | ✓ |
| Household | ✓ | ✓ |
| State | ✓ | ✓ |
| Observations | 776,158 | 776,158 |
| Adjusted $R^2$ | 0.113 | |
| Log Likelihood | | −451,659.400 |
| *Note:* | | *p<0.1; **p<0.05; ***p<0.01 |

Women of age between 15-65 years from NSS rounds 62-68. Individual variables include education, age, marital status. Household information include sector, religion, social group, household size, land holding, consumption in last 30 days, and state level variables include GSDP and industry growth rate.

Table 6: Impact of culture on FLFP

This validates the first two implications, i.e., an increase in culture leads to higher FLFP controlling for other observable factors.

Even though the coefficients are not significant, they have the correct sign here. In the first column implication two is tested and column 2 and three tests the implication 3.

| | *Dependent variable:* | | |
|---|---|---|---|
| | Change in FLFP | | |
| | NSS 64 -NSS 62 | NSS 68- NSS 64 | NSS 68 - NSS 66 |
| Culture IHDS 2005 | −0.117 | 0.110 | 0.090 |
| | (0.069) | (0.098) | (0.082) |
| GSDP | ✓ | ✓ | ✓ |
| Growth rate of Industry | ✓ | ✓ | ✓ |
| Observations | 29 | 29 | 33 |
| $R^2$ | 0.348 | 0.415 | 0.389 |
| Adjusted $R^2$ | 0.206 | 0.288 | 0.276 |

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

State level labor force particiaption from NSS 62-68. Labor force particiaption includes both principle and subsidiary status

Table 7: Impact of culture of change in FLFP

# 4 Alternative Hypotheses

As we have already discussed in the theoretical model, the labor force participation decision depends on several individual and aggregate level variables. In this section, we consider a few such variables in Indian context whose effects on female labor force participation have already been discussed in the literature.

## 4.1 Human Capital

One of the significant determinants of labor market decision irrespective of gender is the accumulated human capital of an agent. With an increase in the stock of human capital, the probability of joining the labor force should increase for an economic agent. However, in India, especially for women the school enrollment and school completion rate for female students has been on the rise along with a decrease in FLFP.

We have considered the gross school enrollment for both primary and secondary between 2007 and 2014 as reported in World Development Indicators data in the World Bank database and we observe an increasing trend for both(See Appendix, figure 4*b*). Gross enrollment in primary (secondary) refers to the ratio of the female in the primary (secondary) education to the total number of female in the primary (secondary) school-going age group. The value can be more than 100% because often female students of an older age would go to school. This implies that the probability of joining the labor force should increase for women in India, which is however not the case.

In the empirical analysis, we use the level of education as one of the explanatory variable to control for the impact of education on labor market decision. But there is one criticism associated with this argument. Since the women who are enrolled in the educational institution are considered as part of *not in labor force*, if more women decide to spend more time in school, then the labor force participation should go down.

We deal with this issue in two ways; first, we show the trend is true across all age groups. Since older women would have less opportunity to go back to school this argument should not work for them. We also repeat the regression dropping the women enrolled in an educational institution (See Appendix, Table 10). The results are robust to this specification as well.

## 4.2 Fertility choice

As mentioned in earlier studies on female labor decision, for women the trade-off is often between home production and market production instead of work and leisure. The labor-leisure choice of women consists of three options, leisure, home production, and labor market participation. As the number of children increases the opportunity cost of labor market participation increases and the agent would be less likely to join the labor force. This implies an increase in fertility rate would mean a decline in labor force participation.

But this is not the case with India female labor market. As in most other developing countries, the fertility rate in India has been decreasing steadily. It has declined from around four births per woman to 2.4 births per woman between 1990 and 2014, which is about 40% decrease over 15 years (See Appendix, figure 4*a*). This implies according to the opportunity cost argument more women should participate in the labor market contrary to the observed data that shows a declining trend.

It is not only the case that fertility rate has gone down in India, but the average childbearing age has also changed. The average age of first birth is 19.9 years. As opposed to 1972 when 22% women would bore children were in their early 30s, whereas it was only 8% in 2006. This would imply the most significant impact of the fall in labor force participation would be seen on relatively young women in their teens or twenties.

A closely related issue is that of the cost of childcare. As family size starts to decrease across the country the informal childcare support has become weaker for women with children. But the formal childcare support has also not developed significantly which makes it harder for women with small children to join the labor force. We consider a proxy for childcare using the size of the household in the empirical analysis.

## 4.3 Income and U-Shaped hypothesis

Another prevailing theory regarding female labor decision is the U-shaped hypothesis which relates income with the probability of labor force participation as discussed before. The income can refer to household income or GDP of the country. In cross country survey and time series survey for many countries as well this U-shaped relationship has been observed.

There are several pieces of evidence against the U-shaped hypothesis in the case of India however. To begin with, the FLFP has been historically low in India unlike many other poor or developing countries. The decline has started from the already low level of FLFP and even with a very high growth rate the trend has not reversed which makes the case of India unique.

Also, the declining trend holds for all income and education group as can be seen in figure 2*a* and figure 2*b*. We control for both household income and GSDP to account for the effect of income on female labor market decision in our empirical exercise and show that our results are robust to all these specifications.

### 4.4 Rate of urbanization

In the recent past, Turkey had a similar experience of declining female labor force participation. FLFP went down from 34% in 1988 to 22% in 2007 but eventually went back to 29.3% in 2014. The decrease in female LFP was accompanied by a high rate of female education, improved structural and social change felicitating women to enter the labor market.

This apparent puzzle in the decline of the labor force participation was due to rapid urbanization in Turkey during the same period. As the country became more urbanized, families moved out of rural areas to settle down in cities where the low skilled labor market had a poor wage rate, and childcare was very costly. As a result low skilled women were forced to stay at home and provide for home production because of the poor labor market conditions. As the process of urbanization slowed and women started to acquire higher education the condition of the low skilled labor market changed. As a result within a few years, the labor force participation began to increase.

That is, however, not entirely the case in India. Post-independence India has faced a high rate of urbanization that has often created enormous population pressure in Indian cities. But as can be seen in the scatterplot (See Appendix, figure 3(c)) of the share of urban population across different States and FLFP show no particular trend. We control for the rate of urbanization using 2001 and 2011 census for all states.

### 4.5 Industry Composition

In recent years in China, the female labor force participation has decreased due to the change in industry composition. One argument is that more female-dominated industries, namely industries where women are more likely to work, experienced negative or slower growth and as a result, the demand for female labor has gone down. Similarly, in the case of India, it is often argued that the female labor force participation is lower due to the low or negative growth rate of the manufacturing sector.

In India, for women with no or little education, the most common occupation is agriculture whereas for women with primary, secondary or college education service sector and manufacturing sectors provide most job opportunities. Even though the agricultural sector is shrinking in India, the service sector has seen phenomenal growth. Women with higher education are more likely to work in service, and hence it is surprising that a growing service sector would be associated with a decrease in FLFP.

In the service sector, women predominantly work in education, mainly primary and secondary school, and the health sector. Even though the growth of these two sectors are lower compared to other industries in the service sector, for example, communication or financial services, the growth rate of education and health sector has been significant compared to the overall growth rate of the economy.

In the manufacturing sector, textile and food processing are the industries that employ the highest share of women workforce. Both these two sectors have seen a significantly high growth rate compared to many other sectors in India. Even though the female-dominated sectors have a reasonable growth rate, it has been reflected in FLFP partly due to a high level of occupation rigidity faced by women. This stickiness in the occupation choice makes it harder for women to find reasonable jobs in other faster-growing sectors in the economy.

As can be seen in the scatterplot of FLFP and growth rate of the industrial sector across different Indian states does not show any noticeable trend or relationship between the two variables. In the empirical analysis, we consider the rate of growth of the manufacturing sector(industry in NSS in the Ministry of Finance, India data) to address this issue.

### 4.6 Demand Side Argument

The demand side argument, as mentioned earlier, refers to the scarcity of jobs available to the women in India. There are several points to be made here. First, the Indian economy has been growing at an astonishing rate of around 7% for a long time, which means more jobs should be made available in the economy. All the more, the highest growth rate is not observed in the manufacturing sector, usually considered as male-dominated, but rather in the service sector which often favors female employment.

As noted in the earlier section, women mostly take jobs in a small part of the service sector, namely education and health sectors, and not in other faster-growing industries like finance, trade, or communication. Since more women are acquiring higher education and the educational gender parity has significantly improved it is unclear whether women do not enter these industries due to lack of demand arising from human capital or other market requirement or due to stigma in part of the employer or the woman's household or neighborhood.

Not only in the service sector the occupation choice for women has remained relatively restricted over the years in all sectors of the economy. Apart from agriculture the primary occupation for women has been, working in the primary or secondary education, custom tailoring, manufacturing of *bidi*(a tobacco product), retail sale and work as housemaid/servants. With the growth of several industries even though the proportion of women across these different occupation has changed but not significantly.

However, the stickiness in the occupation can arise because of many reasons, for example, lack of human capital or other skills. But as mentioned earlier, another reason, as pointed by the women in surveys, is the distance to work. The reason distance is such crucial for work decision might relate to social factors such as safety on the road, family acceptance, etc. rather than only economic factors such as lack of transportation.

The demand-side argument also implicitly assumes wage stickiness for women. Lower productivity of women implies a lower wage. Thus employers cannot hire women worker as women are less likely to accept the jobs at such a low wage which generates a downward wage rigidity for women. This is partly what happened in Turkey during the period of decline in the female labor force. But since this decline is observed across all demographics in India along with higher educational attainment and lower fertility, it is not clear whether there is such a wage rigidity.

We have tried to address all these issues in the empirical analysis by incorporating the growth rate of the industry, the percentage of urbanization and state-level GDP as a proxy for the condition of the labor market. If labor market condition is especially adverse for women but not for men, then only these variables would not be sufficient to justify the declining trend.

Another argument related to this issue is that of improving sex ratio in India. India has one of the lowest females to male ratio in the world, an average of 926 female per 1000 male across all age groups. But the decade of 2001-10 has seen some significant improvement in sex ratio in some states. It can be argued that due to an increasing sex ratio women face more competition at work, and as a result, more women are discouraged from joining the labor force. To address this concern we have also included the state level sex ratio from 2011 census for the empirical exercise.

## 5 Literature Review

Many previous studies have already discussed the role of culture in gender norms and several economic outcomes for women. Here we focus on the literature that examines the role of culture in the labor market decision of women. The following studies were about US female labor market. The labor force participation rate of white married women in the US rose from around 2 percent in 1880 to above 70 percent in the 1990s, and this change had followed an S-shaped path. Several papers used culture as an explanatory variable to explain the S-shaped nature of these dynamics.

Hazan and Maoz (2002) use a labor market decision model where the female agents derive positive or negative utility from working outside the home. The utility is generated by adhering to the social norm which is reflected in the number of women working outside the home. If more women in aggregate work outside the home then the disutility of every single woman decrease and thus social norm directly affects the payoff. In this paper, we also consider that culture or social stigma can directly affect the payoff of the agents but not directly through the number of women in the economy who are working outside the home.

Our paper is closest to Fernandez (2013) where cultural change affects the belief of the agents and is transmitted by social learning. The agents are unsure about the long-run returns from labor force participation and learn by observing the actions taken by other women in an earlier generation. When more women join the labor force, the rate of learning would be faster, and the dynamics would take an S-shape similar to an information diffusion process.

The main problem of applying the framework directly to the Indian context is that in the case of India female labor force participation starts at a meager rate compared to the world average and decreases steadily. Since agents learn socially, over time the belief of the agents would be closer to the actual payoff, i.e., with time the economy would be closer to the "truth". These two facts combined would imply that the long-run payoff is even lower than believed by earlier generations. The later generations would learn from the adverse experiences from the previous generations and would be less likely to join the labor force. Whereas in our model since agents can also learn privately it is not necessarily true that later generations would be more informed.

Also, as more women leave the labor force, the rate of learning should go down, and as a result, the rate of decrease should also go down. As we will mention later, other empirical studies have reported rather a gradual decrease in the FLFP which has increased in the decade of 1990-2009 compared to the decade earlier; thus we can not directly this model to our analysis.

In Fogli (2011) agents are trying to learn about the impact of the decision of working by the mother on her child's development. They exploit the geographical heterogeneity and spatial correlation to argue that an agent can only observe the actions taken by her neighbors in an earlier generation and can update her belief about the "nurture" component of a child's development when the mother works outside the home. In this paper, culture is not explicitly related to the labor market decision, but somewhat social learning from other agents affects the belief and subsequently the decision of the agent.

In this paper, we use the idea that culture affects learning but instead of assuming that the learning is exogenously decided we assume that the agents can choose to learn about the payoff function. We model the learning decision following the *rational inattention* literature. In a stochastic discrete choice problem, Matejka and McKay(2015) use the rational inattention framework and assume that the cost of learning function is the mutual entropy of the prior and expected posterior probability of choice of various actions. Using this cost function, they show that the choice probabilities thus obtained would be similar to that obtained in random utility models, without assuming any structure for the error distribution.

In terms of Indian female labor market also several earlier papers have tried to explain the surprisingly low level and rate of decline of the female labor force participation. There are several hypotheses, namely, a rising level of education, household income, lack of job opportunities, etc.

Increase in the attendance in educational institutions has been considered by Bhalla (2011). They use 2007-08 NSS data to show when adjusted for schooling the drop in FLFP is not that significant. However using later datasets, NSS 2009-10, and NSS 2011-12 round, we find that even after adjusting for schooling the results do not change much.

Several other papers have claimed as women acquire more education they are less likely to join labor force (see Das et al(2006), Kaspos et al(2016) for example). The trend changes only for women who went to college. Afridi et al (2016) argued that this could happen due to an increase in home productivity of the women with the rise in education. They also show that the time spent on household activities have increased significantly over the period.

Related to this issue, other studies claim that the opportunities for educated women are lower because of lack of "acceptable" jobs available (see Klasen et al (2015) for example). For women with a primary and secondary level of education, agriculture is not anymore a lucrative job option because of the low wage rate and increased household income. The lack of growth in the manufacturing sector along with occupational rigidity makes it difficult for these women to work outside the home.

Another reason discussed in the literature is that of an increase in household income. But as Afridi et al (2016) point out the decline in FLFP can be observed since 1987 and post 1990 the rate of decrease has gone up. During the same time, however, India has experienced an average of 7% annual growth rate.

Das et al (2015) explored the role of labor market rigidity and used the cross-state variations in labor market rigidity to explain the low level of participation. Also, the Indian labor market consists of a large informal sector, where female workers are often heavily discriminated against (see Das et al (2006)). The high wage gap makes it less lucrative for women to join the labor force.

Chatterjee et al (2015) argue that the lack of demand for female labor is a significant problem. They show the women face severe restrictions in terms of types of job and location of the job. This finding is again presented in Saha et al (2016), who has conducted a survey on women in India about the difficulty faced by them in terms of job opportunities.

Another concern expressed by several papers has been that of measurement error and the definition of labor force used in NSS data (see Chatterjee et al (2015), Kapsos (2016) for example). There is disagreement about how to classify a person who works in a household farm without pay and a person who does household activities for a non-marketable reason. But the fact that the FLFP has decreased is robust to a different definition of labor force participation.

## 6 Conclusion

In this paper, I discuss the role of culture as a supply-side factor in the declining Indian female labor force participation. By creating a proxy variable to measure the aggregate attitude towards working women, I study the impact of culture on individual decision making. The theoretical model suggests that a less conducive culture can lead to a lower level of learning/ information acquisition by the DM. In the Indian context, this would imply a lower rate of participation and also impacts the rate of change of FLFP. Our empirical analysis verifies these two predictions based on the culture proxies thus defined.

Note that, I do not claim any causal relation between the culture or aggregate belief and decreasing FLFP as the causality is likely to go in both directions. If enough women do not become a business executive, it is possible that opinion regarding the role of women as business executives would worsen due to lack of examples. Instead, we show that the stigma has a significant negative impact on FLFP even after controlling for all relevant variables.

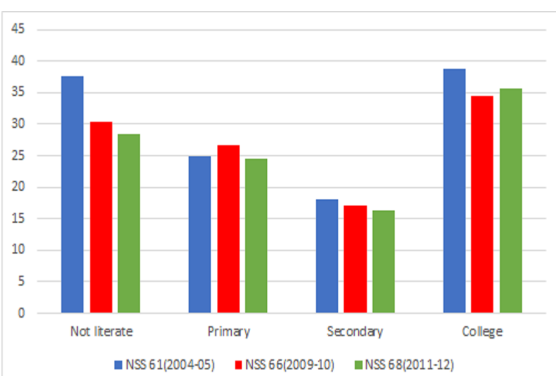
Departing from the literature, I have not explicitly considered the wage gap in our analysis.

There are several problems regarding considering the wage rate directly in our study. In the NSS dataset, a significant proportion of women who are in labor force works in the family farm without a wage. Though we can impute their wage by considering the wage rate of agricultural labors in the relevant market that would not necessarily imply that these women earn the same payoff as those who work for a wage, also, as suggested in our theoretical model if there are different *types* of women with different probabilities of joining the labor force then the women in the labor force can potentially obtain different payoffs than those who are not in labor force and thus wage rate can reflect this heterogeneity of types further biasing our results.

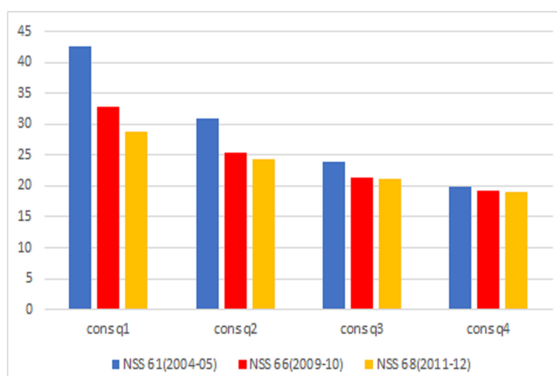
I have already noted that female education is increasing in India even when labor force participation is declining. There can be several hypotheses why this would be the case. If education increases the home productivity relatively more than productivity outside the home, then an increase in the level of education would accompany higher home production and lower LFP. But, a high level of education may also relate to other objectives; for example, education may work as a signal in the highly assortative marriage market in India.

Finally, I have only tried to quantify the impact of culture on FLFP, but have not considered any welfare analysis. For any welfare analysis, I also need to measure the payoff for the women not in the labor force. If lower FLFP implies more leisure for women, then a drop in FLFP would make the individual agents better off. But on the other hand, the economy as a whole may be negatively affected by the lack of *feminization* of the labor force. Thus for welfare analysis, both the micro and macro impacts of the decreasing FLFP is needed, which is beyond the scope of this paper.

# A Data




(a) Female LFP by education group




(b) Female LFP by income group

Figure 2: Change in FLFP across NSS datatsets

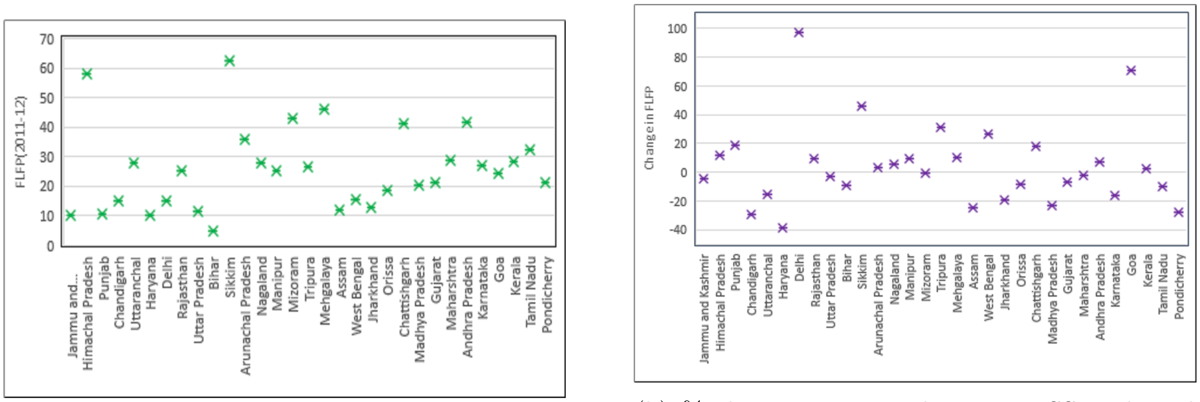
The following table describes the summary statistics for all variables from the four variable in the NSS dataset. Only the individual and household level variables are considered here

| Variable | Categories | Summary Statistics |
| --- | --- | --- |
| Individual characteristics | | |
| Marital Status | Never married | 20.2% |
| | Married | 70.5% |
| | Widowed | 7.6% |
| | Divorced | .7% |
| Education | Not literate | 34.3% |
| | Below primary | 13.1% |
| | Primary | 14.1% |
| | Middle | 15.3% |
| | Secondary | 10.5% |
| | Diploma | 2.8% |
| | Graduate | 3.5% |
| | Post graduate | .8% |
| Age | N/A | mean = 34.73 years<br>median 33 years |
| Household characteristics | | |
| Sector | Rural | 60.3% |
| | Urban | 39.7% |
| Social Group | ST | 12.9% |
| | SC | 15.5% |
| | OBC | 37.6% |
| | Other | 34% |
| Household size | N/A | mean = 5.6<br>median 5 |
| Land holding | N/A | median = [.02, .2] hectares |
| MPCE | N/A | mean = Rs. 5749.823<br>sd = Rs. 110743.3 |

Table 8: Summary statistics for NSS data

# B Emprics: State level heterogeneity

The following shows state-level heterogeneity in the constructed *culture* variable for both IHDS 2005 and 2012. A positive value of change will imply a more favorable condition for FLFP in 2012 compared to that of 2005.




(a) FLFP in NSS 68 round(2011-12)

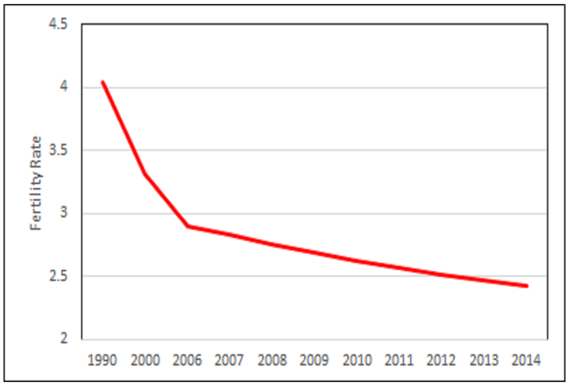
(b) % change in FLFP between NSS 66th and 68th round)

Figure 3: State Level Heterogeneity in FLFP

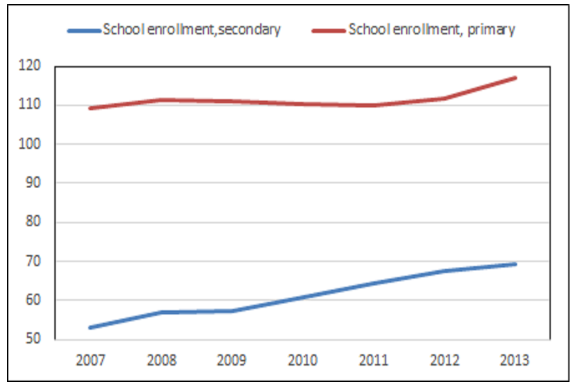
| State | IHDS 2005 | IHDS 2012 | change |
|---|---|---|---|
| JAMMU & KASHMIR | 0.4436291 | 0.4445473 | 0.0009181859 |
| HIMACHAL PRADESH | 0.5278341 | 0.5073265 | -0.0205075823 |
| PUNJAB | 0.4618667 | 0.4494701 | -0.0123965864 |
| CHANDIGARH | 0.4931677 | 0.4999734 | 0.0068057118 |
| UTTARANCHAL | 0.4540254 | 0.4269950 | -0.0270304100 |
| HARYANA | 0.3563355 | 0.3931978 | 0.0368623483 |
| DELHI | 0.4808777 | 0.4379390 | -0.0429387514 |
| RAJASTHAN | 0.3051651 | 0.4032481 | 0.0980830897 |
| UTTAR PRADESH | 0.3079084 | 0.3706631 | 0.0627547204 |
| BIHAR | 0.3156195 | 0.3469460 | 0.0313265080 |
| SIKKIM | 0.7401786 | 0.5763954 | -0.1637831626 |
| ARUNACHAL PRADESH | 0.8131953 | 0.3837833 | -0.4294119751 |
| NAGALAND | 0.5853295 | 0.6135569 | 0.0282273660 |
| MANIPUR | 0.5545506 | 0.5668748 | 0.0123242569 |
| MIZORAM | 0.6069907 | 0.6377104 | 0.0307196970 |
| TRIPURA | 0.6900595 | 0.4732892 | -0.2167703325 |
| MEGHALAYA | 0.6584979 | 0.7087951 | 0.0502972107 |
| ASSAM | 0.4346871 | 0.3391178 | -0.0955693293 |
| WEST BENGAL | 0.4485996 | 0.4776707 | 0.0290710443 |
| JHARKHAND | 0.4076054 | 0.3372462 | -0.0703592007 |
| ORISSA | 0.4265461 | 0.3807300 | -0.0458161325 |
| CHATTISGARH | 0.3752241 | 0.4541175 | 0.0788933659 |
| MADHYA PRADESH | 0.2858951 | 0.3945528 | 0.1086576985 |
| GUJARAT | 0.4344991 | 0.4321534 | -0.0023457478 |
| DAMAN & DIU | 0.4374691 | 0.4849630 | 0.0474938604 |
| D & N HAVELI | 0.4231481 | 0.4318604 | 0.0087122231 |
| MAHARASTRA | 0.4620844 | 0.3883261 | -0.0737582878 |
| ANDHRA PRADESH | 0.4540199 | 0.4080450 | -0.0459748602 |
| KARNATAKA | 0.4751294 | 0.4241776 | -0.0509517322 |
| GOA | 0.5331426 | 0.5070638 | -0.0260788155 |
| LAKSHADWEEP | 0.4989702 | 0.4844816 | -0.0144885830 |
| KERALA | 0.6214703 | 0.4876746 | -0.1337956395 |
| TAMIL NADU | 0.5638584 | 0.5494501 | -0.0144082816 |

Table 9: IHDS culture variable by State

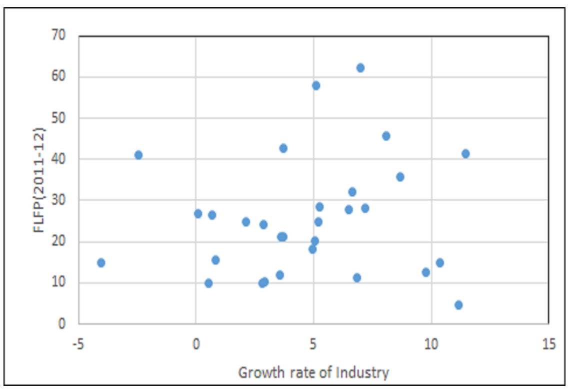
# C Alternate Hypotheses



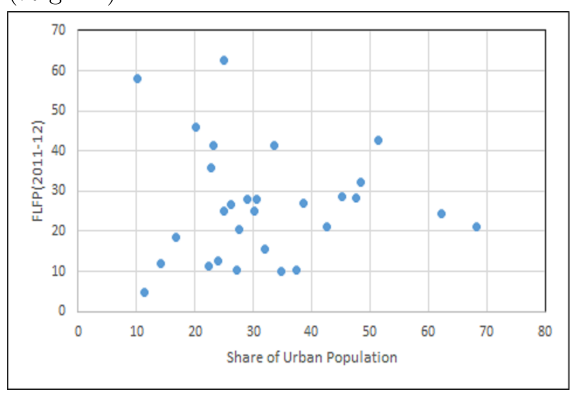

(a) Fertility Rate, total (births per women)




(b) School enrollment, primary and secondary, female (% gross)




(c) FLFP and the Rate of Growth of Industry




(d) FLFP and Share of Urban Population

Figure 4: Alternate Hypotheses